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Real-time management of the waterflooding process using proxy reservoir modeling and data fusion theory

Farzad Hourfar[a,*,1], Behzad Moshiri[a], Karim Salahshoor[b], Ali Elkamel[c,*]

[a] Control & Intelligent Processing Center of Excellence (CIPCE), School of Electrical & Computer Engineering, University of Tehran, Tehran, Iran
[b] Department of Automation & Instrumentation Engineering, Petroleum University of Technology, Ahwaz, Iran
[c] Department of Chemical Engineering, University of Waterloo, Ontario, Canada

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ABSTRACT

Waterflooding is the use of water injection to enhance the oil recovery in mature oil reservoirs. In this paper an adaptive algorithm has been introduced for waterflooding management in oil reservoirs based on proxy modeling technique. The presented approach is capable to handle the time-varying nature and the inherent nonlinearity of the complex process. In addition, any variation either in market prices or in operational costs is compensated by the designed adaptive controller to fix the obtained profit (here, the net present value: *npv*) at a desired achievable value. The observed outcomes on 10th SPE-Model#2 benchmark case study have shown that by using this algorithm, any feasible desired trajectory for the expected benefit can be satisfied during the waterflooding-based production. Since the suggested controller has adaptive structure, it can be re-adjusted continuously in each time-step, using available operational data, to take into account the reservoir dynamical variations as well as the external disturbances to present an acceptable performance. By including a monitoring module in the algorithm structure based on data fusion technique, the updated profitability/productivity status of the reservoir is estimated. By using this information the *npv* setpoint induced to the closed-loop system can be automatically re-adjusted such that it always remains in an acceptable and reasonable range. In conclusion, the proposed methodology is an applicable solution for fairly profit-sharing in different kinds of contracts. In other words, the gained profit can be appropriately allocated to the shareholders according to the contractual obligations or a defined *npv* trajectory while considering the current condition of the reservoir. This strategy helps to prevent from ultra-production in a specific period of time by the clients or contractors which may lead to an unexpected reduction in the share of other parties in the reservoir life-cycle.

1. Introduction

For reducing the gap between demand and sources of hydrocarbon-based energy, an effective solution is increasing the oil recovery factor in existing reservoirs. The average recovery factor may disappointingly come down to about 15% in complex reservoirs (Sarma, 2006; Golder Associates, 2000). However; by using secondary production approaches such as waterflooding- in which water is injected into the reservoir for conducting the oil toward production wells for more efficiency- up to 70% of the hydrocarbon can be recovered theoretically (van den Hof et al., 2009). So, different aspects of waterflooding modeling, control and optimization studies, have recently attracted much attention by the researchers (Sarma et al., 2006; Shirangi and Durlofsky, 2015; Grema and Cao, 2016; Sorek et al., 2017).

Although hydrocarbon production is a complex large-scale dynamical process, the operators in the fields mostly manage it just based on their own experiences. Fortunately, widespread applications of advanced instrument and control devices have increased the opportunity to optimize the oil production using model-based control and optimization techniques (Jansen et al., 2008). Nowadays, intelligent reservoirs are generally equipped with appropriate sensors and actuators to monitor the wells and reservoir conditions as well as to control the fluids flow of the producing and injecting wells. It has been perceived that applying advanced mon-

* Corresponding authors.
E-mail addresses: f.hourfar@ut.ac.ir (F. Hourfar), aelkaeml@uwaterloo.ca (A. Elkamel).
[1] Present address: Department of Chemical Engineering, University of Waterloo, Ontario, Canada.

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itoring and control systems in reservoirs can significantly increase the hydrocarbon recovery (Glandt, 2005).

Closed-loop reservoir management (CLRM) is a popular methodology, which take into account the reservoir observed data as well as the information obtained from model-based simulations, to design the suitable optimal control strategies (Foss, 2012). Generally, the manipulated variables in a reservoir are bottom-hole pressures (*bhp*) or flow-rates of the wells, and the ultimate goal in CLRM is to maximize an objective function which is usually selected as the net present value (*npv*) of the recovery process subject to the operational constraints. In other words, optimization in oil reservoirs can be performed by adjusting optimum injection and production rate settings for maximizing the *npv* as a well-known profitability index. In model-based optimization approaches which use open-loop configuration, the reservoir models are supposed to be perfect in presenting all existing dynamics of the system (Asadollahi and Naevdal, 2009). Consequently, open-loop techniques, such as dynamic optimization, suffer from loss of robustness against uncertainties and may deduce suboptimal or even non-optimal results (Brouwer and Jansen, 2004). On the other hand, robust optimization techniques, which use a set of reservoir realizations for considering different types of probable geological models, have been introduced to cope with the uncertainties (van Essen et al., 2009). However, these methods' principle assumption, which is all existing reservoir characteristics and production behaviors are presented by the developed realizations, is somehow unrealistic (Grema and Cao, 2016). That is to say, the set of various realizations may not be completely successful to reflect the real reservoir dynamic which is needed for an efficient optimization process.

From another point of view, in model-based dynamic reservoir optimization using direct methods, it is possible to define the optimal control problem in the framework of nonlinear programming (NLP) (Binder et al., 2001). In this methodology, the optimizer seeks for the solution sequentially. It means that a control profile is computed at each step and then the obtained profile is simulated for investigating the results. This sequential-optimization process is generally known as single shooting (SS) (Jansen, 2011). For instance, generalized reduced gradient (Kraaijevanger et al., 2007), and augmented Lagrangian (Chen et al., 2010) are common gradient-based methods for dealing with NLP's, specially applied in reservoir optimization. In these techniques, gradients of the objective and function evaluations should be computed. In addition, existence of operational constraints forces some limitations on *bhp*'s and flow-rates of the wells. Function evaluations is the technical term for presenting the dynamic behavior of the reservoir and can be achieved using valid simulators. Furthermore, objective gradient can be calculated via adjoint techniques. However, existence of nonlinear constraints can dictate additional adjoint simulations and increase the computational load of such techniques. As a result, methods to lump reservoir output constraints, such as limitation on the volume of the produced water, into a single constraint have been developed to evade from extra adjoint computations (Suwartadi et al., 2011; Kourounis et al., 2014). Nevertheless, these approaches may induce extra approximations as well as parameters retuning. To handle the mentioned problem related to the output constraints, direct method for dynamic optimization in oil reservoirs based on multiple shooting (MS) technique, has been proposed in (Codas et al., 2015). But, applying this approach requires an intense interaction between optimizer and simulator, which causes to a huge computational load. In addition, to achieve an efficient MS implementation, parallel-computing facilities and extensive-memory should be available. Moreover, several research on reservoir optimization and production management based on proper orthogonal decomposition (van Doren et al., 2006) and trajectory piecewise linearization (Cardoso and Durlofsky, 2010; Gunnerud and Foss, 2010) have tried to develop methods in which the search-space and also memory requirements decrease.

Obviously, all model-based approaches applicable for the production management in the hydrocarbon reservoirs require accurate reservoir models. A real reservoir can expose totally different behaviors compared to the assumed models. As a result, by just relying on the outcomes of cumbersome model-based optimization techniques, which have been validated in simulation mode while ignoring the real-time production data, the optimization goals may not be achieved in the real applications. This fact has origin in continuous time-varying dynamics of the reservoir as well as the impacts of unknown geological and financial uncertainties during the operation. In other words, in the presence of uncertainties, implementation of appropriate control strategies for optimizing purposes is completely a challenging task. Hence, although many contributions which apply different control techniques use reservoir models to identify the optimal response (Sarma et al., 2005; Jansen et al., 2009), the obtained results are not applicable in practice since the considered models are rarely predictive.

When a batch of new information such as recent production data, up-to-date well logs, and new seismic data are provided during the operation in the oil fields, the utilized reservoir model(s) may be updated by history matching process. Therefore, new optimization calculations would be done based on the updated reservoir models (Foss and Jensen, 2011). Yet, even history-matched models may not be able to forecast the future behavior of reservoirs precisely (Tavassoli et al., 2004). Consequently, instead of periodically updating of the reservoir models via history matching process, closed-loop control strategies based on last measured production data have been introduced (Foss and Jensen, 2011; Jansen et al., 2008).

In other words, besides utilizing complicated model-based methods for optimization objectives, either gradient-based or derivative-free techniques (Chen et al., 2008; van Essen et al., 2011; Ciaurri et al., 2011; Giuliani and Camponogara, 2015; Wang et al., 2016), exploring for more realistic solutions, which profit from simplicity in comparison with fully model-based optimization approaches, is an active research area in this domain (Foss and Jensen, 2011; Shuai et al., 2011; Reynolds and Oliveira, 2013; de Holanda et al., 2015). To this aim, there have been some attempts to consider the CLRM as a regulatory feedback control problem (Grema and Cao, 2016; Güyagüler et al., 2010; Grebenkin and Davies, 2010). Generally, the characteristic of direct feedback-control robustness against unknown reservoir uncertainties is one of the strengths of this approach (Chen et al., 2012). It means that by applying feedback control strategy, the performance becomes less sensitive to model errors and inherent uncertainties of the oil reservoirs. The obtained results in (Dilib and Jackson, 2013; Dilib et al., 2015) demonstrate that closed-loop control methodology which is based on direct feedback between reservoir monitored variables and production flows can lead to near optimal achievements in oil reservoirs. Closed-loop feedback control of the reservoir can also alleviate the effect of existing geological uncertainties on reservoir behavior.

Based on the above explanations, transforming the complicated reservoir optimization problem to the regulatory control framework is among the possible solutions which can have acceptable efficiency, simplicity, and potential of being easily implemented in practice. On the other hand, due to the nature of an oil reservoir and different uncertainty sources, field noises and disturbances during the operation, self-optimizing-control (SOC) strategy can be a proper candidate for optimizing the waterflooding process under certain conditions (Grema and Cao, 2016). It has been proved that if the controlled variables are selected appropriately in SOC framework and also regulated such that they remain constant during the